



openAMUNDSEN-DA v0.9: an ensemble based snow data assimilation framework for the open source snow hydrological model openAMUNDSEN

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Abstract. Satellite and in-situ snow observations are increasingly available, but their assimilation into physically based snow modeling within a reproducible workflow from data preprocessing to model diagnostics remains a challenge. We present openAMUNDSEN-DA v0.9, an open source ensemble based snow data assimilation framework coupled to the fully distributed snow hydrological model openAMUNDSEN. The new framework enables sequential particle filter updates within a configured, traceable workflow while keeping the original snow model setup separate from data assimilation settings. Prior uncertainty is represented by perturbing the meteorological forcing, ensuring each ensemble member follows a physically consistent simulation trajectory. The workflow covers observation preprocessing, event scheduling, ensemble execution, likelihood based member weighting, effective sample size diagnostics, resampling, rejuvenation, posterior generation, benchmarking, and the production of plots, maps and concise reports. Supported observation types include station snow depth and snow water equivalent, and satellite based snow cover fraction, wet snow fraction, and wet snow line altitude. For each assimilation experiment, observation specific model equivalents and uncertainty settings are defined in the project configuration. We illustrate the capabilities of the new framework in a case study from the Rofental research catchment (Ötztal Alps, Austria), sequentially assimilating in situ snow depth, satellite snow cover and wet snow observations.

1 Introduction

Seasonal snow in alpine catchments is an essential water reservoir, a control on runoff timing and an important boundary condition for hydrological forecasting, hazard assessment and climate impact studies (Beniston et al., 2018; Kotlarski et al., 2023; Dumont et al., 2025). However, its spatial distribution and seasonal evolution remain difficult to model because mountain terrain creates strong gradients over short distances in precipitation, radiation, wind exposure, vegetation and hence, the spatial pattern of snow accumulation and available melt energy (Strasser et al., 2011; Largeron et al., 2020). Sources of uncertainty in snow modeling include the meteorological forcing, the difficult choice of the best model structure, model parameters and/or the scale mismatch between model, data resolution and temporal and spatial variability of the simulated processes (Helmert et al., 2018; Largeron et al., 2020; Günther et al., 2020, 2019; Rottler et al., 2026). As a result, snow hydrological models can deviate significantly from observed snow states during critical accumulation and melt periods, especially when errors in precipitation phase and/or amount, or in complex lateral redistribution processes, persist over longer periods. In addition



to modeled data, many observation time series from snow stations are available and a wealth of satellite based snow cover products exist. However, there still is a need for model frameworks that can integrate the available observational snow data into model simulations, be it local measurements, preprocessed grids or satellite derived spatially distributed fields. Snow data assimilation (DA) addresses this issue by combining model simulations with observations in a statistically consistent update framework. However, the quality of the snow simulation including DA not only depends on the DA algorithm itself, but also on the quality of the observational data, how those data are preprocessed, how uncertainty is represented, how simulation and observation are compared and whether the resulting workflow can be automated, reproduced and transferred to other areas.

In general, DA has a long history in the geosciences (Carrassi et al., 2018) and snow hydrological applications have developed along several methodological lines, including Kalman filter and particle filter (PF) approaches, smoother based reanalysis methods and increasingly modular or operational systems (Helmert et al., 2018; Largeron et al., 2020). Early snow DA studies demonstrated the potential of assimilating passive microwave snow water equivalent (SWE) (Sun et al., 2004), fractional snow cover (Andreadis and Lettenmaier, 2006) and point scale snow observations into land surface and hydrological models (Slater and Clark, 2006; Leisenring and Moradkhani, 2011). Later work showed the value of particle batch smoothers for SWE reanalysis (Margulis et al., 2015), forcing perturbation formulations for physically based snow models (Magnusson et al., 2017) and PF approaches that preserve nonlinear snowpack trajectories while updating ensemble probabilities (Piazzi et al., 2018; Chopin and Papaspiliopoulos, 2020). PF applications remain challenging in high dimensional geophysical systems because of weight degeneracy and representation errors (Van Leeuwen, 2009; van Leeuwen, 2015). Recent snow DA systems adopt different assimilation strategies depending on the intended use. CrocO, for example, uses a spatialized PF framework with global and local variants for snowpack observations (Cluzet et al., 2021), while MuSA provides a flexible, modular, open source toolbox with multiple filters, smoothers and joint assimilation options (Alonso-González et al., 2022). FSM2OSHD, on the other hand, is the snow model component of the broader framework operated by the Swiss Operational Snow-Hydrological Service (OSHD), with recent work combining station and Sentinel-2 snow cover information in fully distributed simulations (Mott et al., 2023; Oberrauch et al., 2026). These systems provide important context for modern ensemble snow DA, but they also show that frameworks typically are organized around certain snow models and observation products and are developed for specific scales and research or operational applications. Having reviewed the strengths and limitations of existing snow DA systems, we conclude that new frameworks should be open source, flexible, and easy to apply for both research and operations. They should provide a fully documented, reproducible workflow that includes the preprocessing of satellite and in situ snow observations, ensemble execution and sequential assimilation configured and documented within a single project structure.

Here we present openAMUNDSEN-DA (v0.9), an open source snow data assimilation framework coupled to the open source snow hydrological model openAMUNDSEN (Strasser et al., 2024). openAMUNDSEN provides fully distributed snow simulations with configurable process representations for snow and ice melt, lateral snow redistribution, and snow canopy interaction. openAMUNDSEN-DA now enables an end to end, traceable workflow for ensemble based DA of snow observations, covering preprocessing of the observation data sets, ensemble execution, sequential assimilation, posterior materialization, diagnostics, plots and maps. Motivated by the need to preserve physically consistent model trajectories in a complex snow model structure while avoiding direct manipulation of the internal snowpack states (Charrois et al., 2016; Cluzet et al., 2021), we



60 adopted a sequential PF (Gordon et al., 1993; Chopin and Papaspiliopoulos, 2020; Piazzini et al., 2018), whereat prior uncertainty is represented with a forcing formulation in which meteorological input data sets are perturbed (Evensen et al., 2022). openAMUNDSEN-DA supports the assimilation of snow observations of several types in a single sequential workflow including in-situ snow observations and satellite derived fractional snow covered area (fSCA), wet snow fraction (WSF) and wet snow line altitude (WSLA). The usage of fSCA has a long history in snow DA, ranging from early MODIS based applications
 65 (Andreadis and Lettenmaier, 2006) to modern ensemble based fSCA assimilation (Aalstad et al., 2018). WSF and WSLA based on Sentinel-1 observations provide complementary constraints on the melt state evolution (Marin et al., 2020; Rottler et al., 2024; Cluzet et al., 2024). With regard to in-situ snow observations, explicit attention is given to observation uncertainty and the limits of point scale representativeness in complex terrain (Slater and Clark, 2006; Grünwald and Lehning, 2015; Oberrauch et al., 2024, 2025). openAMUNDSEN-DA includes support for parallel processing and regionalized execution options
 70 enabling the processing of large areas without changing the overall application workflow. We showcase the configuration options, event handling, diagnostics and spatial outputs of openAMUNDSEN-DA through an application in the Rofental research catchment (Ötztal Alps, Austria).

2 General structure and architecture

openAMUNDSEN-DA is designed to make ensemble snow data assimilation compatible with existing openAMUNDSEN
 75 model configurations and traceable across assimilation events. Furthermore, it is portable between computing environments, extensible to new observation workflows and scalable to larger domains. Hence, a central design choice is that openAMUNDSEN remains fully distributed within each model domain, whereas the sequential DA update is driven by domain scale metrics that can be compared consistently between observations and ensemble members (van Leeuwen, 2015; Janjić et al., 2018). We designed the architecture of the framework keeping the configuration of a DA experiment separate from the generic soft-
 80 ware routines that execute it. In the following, we present a description of the DA framework structure and architecture. The PF formulation, perturbation model, likelihood calculation, resampling, rejuvenation and score definitions are presented in Sect. 3.

Developing openAMUNDSEN-DA we couple two open source frameworks (Fig. 1b). openAMUNDSEN is the host snow hydrological modeling framework, providing distributed simulations of the seasonal snow cover evolution in complex terrain (Strasser et al., 2024). openAMUNDSEN-DA adds the DA workflow around this host model: it prepares the snow observational
 85 data, creates and runs ensembles, compares model equivalent metrics with observations, updates ensemble probabilities, propagates posterior members and generates diagnostics. The coupling is organized so that the existing openAMUNDSEN snow model setup and configuration structures remain unchanged, while data assimilation choices are added in a separate project configuration layer. This separation keeps the snow model configuration, parameters and internal state variables distinct from the DA layer. The prior uncertainty is introduced by the meteorological forcing perturbation.

90 The main design scope of openAMUNDSEN-DA is a reproducible domain scale sequential PF workflow, rather than a general multi algorithm DA toolbox or a localized or spatialized PF system. Accordingly, openAMUNDSEN-DA is a natural complement to existing snow DA frameworks, such as MuSA's broader algorithmic toolbox (Alonso-González et al., 2022)

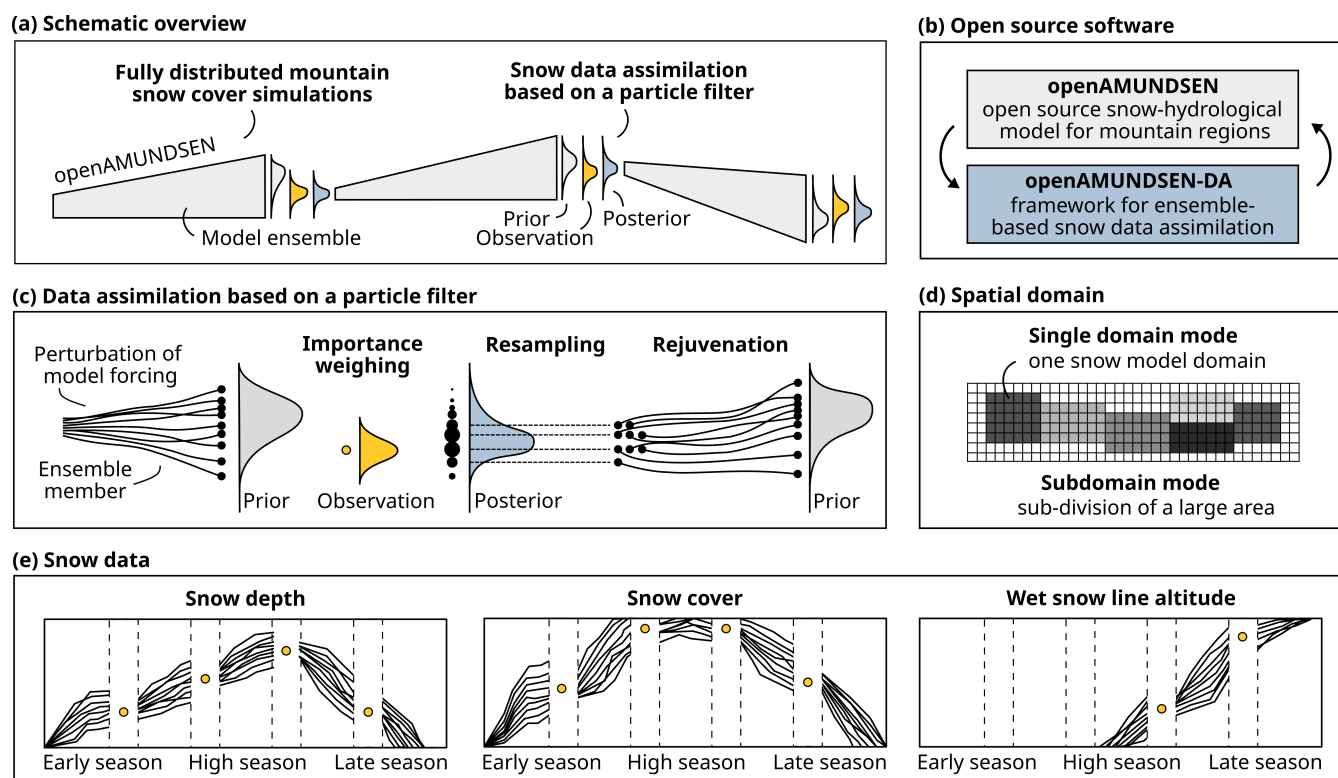


Figure 1. Schematic overview of the architecture and execution workflow of openAMUNDSEN-DA: (a) ensemble based snow modeling including sequential data assimilation, (b) the coupling between openAMUNDSEN and openAMUNDSEN-DA, (c) the particle filter stages, (d) single domain and subdomain execution modes and (e) the supported snow observation types. At each assimilation event, the prior is the ensemble distribution before observation-based likelihood weighting. The posterior is the distribution of the weighted ensemble after comparison with the observation. Observation preprocessing, ensemble propagation, weighting, resampling, rejuvenation, diagnostics and reporting are organized as reproducible workflow stages.

and CrocO's spatialized PF approach (Cluzet et al., 2021), offering additional approaches to the snow modeling community. At the implementation level, our DA framework follows the configuration driven philosophy of openAMUNDSEN. Generic functional code is kept in the Python package, while experiment specific decisions are formulated and stored in YAML files. This split is important because the modeled domain, observation products, uncertainty assumptions, assimilation dates, output variables, maps and plots can be inspected and rerun without modifying the source code, a transparency requirement for reproducible model comparisons (Menard et al., 2021). It also supports extensions: new observation preprocessors, data assimilation variables, diagnostics or project workflows can be added without changing the basic setup and project organization.

For the user, openAMUNDSEN-DA is operated through command families rather than through interactive scripts. A standard pipeline runs a complete project in one pass to support repeated experiments, while lower level commands remain available for observation data preprocessing, plotting, mapping, benchmarking, reporting, and running subdomain workflows. The



software is distributed as an installable Python package and as a Docker image. The Docker image bundles the geospatial, numerical and plotting routines and the openAMUNDSEN model as well as the openAMUNDSEN-DA dependencies required for a complete run. It also includes the Rofental example data (see Sect. 4) as a starting point for new DA projects. This containerized execution minimizes differences in operating systems and binaries across users, enables reproducible runs on workstations and servers and makes the same documented workflow usable for tutorials, local experiments and larger computing environments. Computational performance is addressed at two distinct levels. The coupled openAMUNDSEN model provides kernel level acceleration through Numba compiled numerical routines for computationally intensive physical model components. openAMUNDSEN-DA then exploits the full CPU capacity by worker configurations through controlled process level worker pools, so that optimized model kernels are used within each realization while realizations and subdomains are distributed across the available processor cores with explicit worker caps.

Folder configuration and hierarchy of openAMUNDSEN-DA

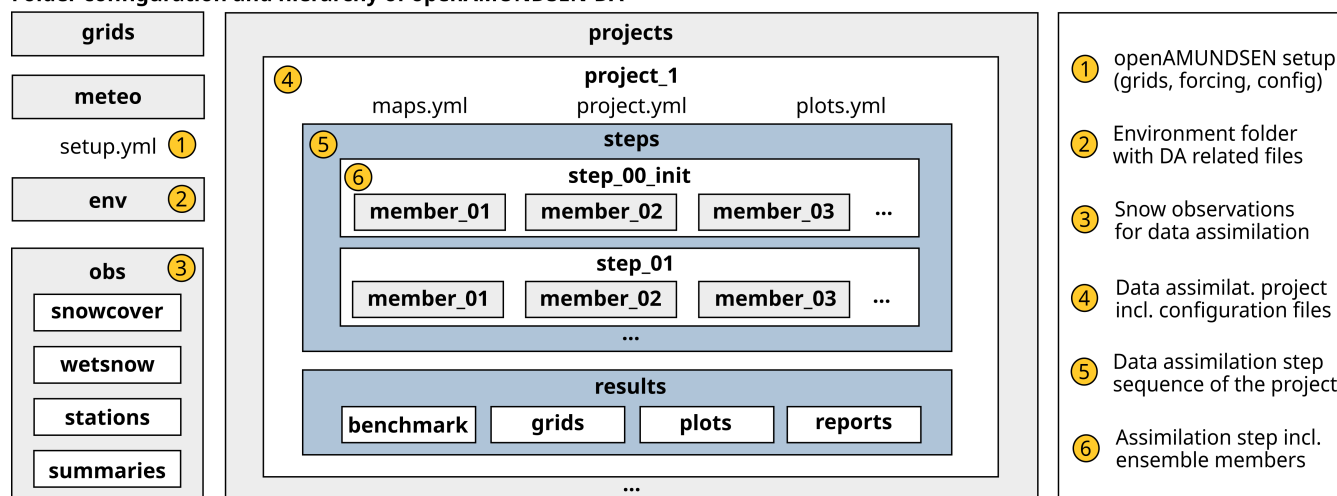


Figure 2. Folder and configuration hierarchy of an openAMUNDSEN-DA setup: (1) openAMUNDSEN grids, meteorological forcing and snow model configuration file, (2) auxiliary environment files for data assimilation, (3) snow observations used in the data assimilation, (4) the data assimilation project directory containing DA configuration files and the results of the benchmark diagnostics, grids, plots and reports, (5) the sequence of assimilation steps, and (6) the prior and posterior ensemble members in each step.

An openAMUNDSEN-DA experiment is organized through four conceptual levels: setup, project, step and member (Fig. 2). The collection of the openAMUNDSEN setup inputs, auxiliary environment files and snow observation inputs form the data basis for the simulation (Fig. 2, item 1–3). The DA project folder contains data assimilation experiments using the openAMUNDSEN snow model setup, including the project time span, DA configuration, observation product settings, assimilation events, map and plot recipes as well as result groups (Fig. 2, item 4). Each DA project is materialized as generated assimilation steps and prior and posterior ensemble members (Fig. 2, item 5 and 6), whereby each member is one openAMUNDSEN model run and particle in the PF.



120 The given hierarchy also represents a configuration ownership rule. The setup YAML file remains a pure openAMUNDSEN configuration file in the shared openAMUNDSEN setup. In the project folder, the 'project.yml' owns data assimilation configuration, observation mappings, uncertainty settings, benchmark settings and assimilation events, while 'maps.yml' and 'plots.yml' own project specific map and plot recipes. Step YAML files are generated inside the step level and contain step local openAMUNDSEN settings, while member folders inside each step store the prior and posterior model runs used for the update.

125 An assimilation event is a dated, project level instruction to select the observation type and associated observed variable for a single sequential update. It determines which observation type is read, which model observation comparison is computed, how member weights are evaluated and whether the resulting posterior is passed forward to initialize the next step. Keeping this schedule in the project configuration makes the sequence of updates transparent and separates the DA experiment design from snow model configurations. Before expensive model propagation starts, the project runner validates configured events, required

130 model outputs, observation summaries, per step observation files and station inputs, so inconsistent experiment definitions fail early with explicit missing input logging rather than producing incomplete DA outputs.

In general, a DA project pipeline follows a prediction update cycle (Fig. 1 a and c). Prior to a project run, satellite and station observations are summarized into DA ready summaries. At each assimilation step, openAMUNDSEN-DA generates a prior forcing ensemble, propagates the openAMUNDSEN ensemble members, computes model equivalent metrics for the selected

135 observation type and recursively updates the particle weights. Resampling is only done when the effective sample size (ESS) is below a user-defined threshold (Sect. 3) (Moradkhani et al., 2005; Abbaszadeh et al., 2018). The event analysis is the weighted distribution before resampling. If resampling is triggered, a materialized ensemble initializes the subsequent propagation and its weights reset uniformly. If resampling is skipped, the member trajectories and their normalized weights are carried into the next update. Rejuvenation then provides an event-specific process-noise refresh for the next propagation window. This process

140 is repeated until the project end date. The open loop simulation is retained as a reference baseline without assimilation. Below is an excerpt from a 'project.yml' file specifying the WSLA assimilation on May 3, 2023:

```
data_assimilation:
  assimilation_events:
    - date: '2023-05-03'
      observation_time: '2023-05-03T05:26:24Z'
      variable: wet_snow_line
      product: WETSNOW
```

For satellite observations, openAMUNDSEN-DA resolves the acquisition time from the CF time coordinate, raster metadata, sidecar metadata, a configured filename parser or a tracked provenance manifest, in that order. If no timestamp is available,

150 the software uses midnight UTC as a backward-compatible fallback, emits a warning and records the reduced time quality. Resolved timestamps are converted to a timezone-aware UTC representation and matched to the unique nearest model time step. Ties and offsets larger than half a model time step are rejected. Instantaneous snow depth, snow water equivalent and liquid water fields at the matched model time are used by the observation operator, so observation time and matched model time remain distinct and traceable.



155 Observation support follows the hydrological scale concept in which support denotes the spatial footprint, temporal inte-
 gration window and retrieval valid part of the domain represented by an observation or observation derived metric (Blöschl
 and Sivapalan, 1995). Support mismatch can be a problem in DA because representation errors arise when the modeled val-
 ues entering the likelihood represent a different spatial or temporal sample than the observation (van Leeuwen, 2015; Janjić
 et al., 2018). Accordingly, we aim to use support aware comparisons in openAMUNDSEN-DA comparing snow model runs
 160 (ensemble members) to observations using metrics that take into account the effective observation support. In practice, satel-
 lite derived snow metrics are aggregated only over pixels that are valid for the acquisition. Clouds, no data areas, land cover
 exclusions and product specific masks are applied consistently to the observations and model outputs, ensuring that the same
 areas are compared to each other (De Lannoy et al., 2012; Aalstad et al., 2018). Point observations (e.g., station snow depth)
 are treated as locally representative with explicit limits on how far they inform grid cells or catchment averages, reflecting
 165 the well-documented mismatches between flat field snow depth measurements and heterogeneous alpine terrain (Grünewald
 and Lehning, 2015). When multiple stations are assimilated, they contribute uncertainty weighted to the comparison with the
 model simulation, so that trusted stations have greater influence on the update, while more uncertain stations have less. Across
 observation types, openAMUNDSEN-DA treats masking, uncertainty layers, land cover penalties and validity checks as part
 of the workflow. Missing or invalid observations are therefore handled before the PF update and each DA step receives explicit,
 170 traceable observational data instead of ad hoc product specific inputs.

The framework produces diagnostics and reports throughout the project, including documentations on weights, ESS, re-
 sampling, member metadata, temporal ensemble summaries, observation summaries, benchmark tables, plots, and maps. The
 same traceability extends to gridded DA outputs: raster data with open loop values, ensemble statistics, increments and event
 weighted analysis values for downstream spatial analysis, all of which can be written to NetCDF files as variables or to single
 175 TIFF files. The documented diagnostics and outputs are particularly important for a scientific workflow because users can in-
 spect which observation was used, how strongly it constrained the ensemble, which members were selected and how posterior
 trajectories and spatial diagnostics changed relative to the open loop.

For large-scale applications, openAMUNDSEN-DA supports the controlled parallel execution of multiple domains (subdo-
 main mode) (Fig. 1d). The subdomain mode partitions a large spatial area into regional units (e.g., headwater catchments) that
 180 are processed independently. This improves computational efficiency and also reduces the effective dimensionality of each PF
 update, mitigating weight degeneracy (Snyder et al., 2008; Bengtsson et al., 2008; Rebeschini and Handel, 2015; Odry et al.,
 2022). In its current form, the subdomain mode should be regarded as the regionalized execution of independent DA problems
 rather than as a formally localized PF. In general, parallel execution is used where workflow tasks are independent, for ex-
 ample, across ensemble members, diagnostic products or independent rendering tasks, while worker counts can be limited to
 185 match available processor and memory resources. Computational resources are monitored, e.g. CPU usage, memory pressure,
 filesystem usage and project size growth during a DA experiment, making computational documentation part of the project
 record.



3 Data assimilation

The assimilation of snow observations in openAMUNDSEN-DA is based on a sequential PF at the domain scale (Fig. 1c).
 190 Each ensemble member is a single openAMUNDSEN model run and a DA update selects best fitting members rather than directly modifying internal snowpack states. In general, PFs provide a sequential Monte Carlo representation of nonlinear and non Gaussian Bayesian filtering problems (Gordon et al., 1993; Arulampalam et al., 2002). This approach is well suited to multilayer snow models because member weighting avoids Ensemble Kalman filter (EnKF) state corrections, enabling nonlinear and multivariate snowpack trajectories to be selected without physically inconsistent updates or averaging incompatible snow
 195 states and layer structures (Magnusson et al., 2017; Piazzini et al., 2018). In openAMUNDSEN-DA, meteorological forcing perturbations sample uncertainty, while the snow model remains deterministic and internal model parameters are not perturbed (Evensen et al., 2022). For an observation y at assimilation date k , the Bayesian filtering update can be written as:

$$p(x_k | y_{1:k}) \propto p(y_k | x_k) \times p(x_k | y_{1:k-1}), \quad (1)$$

where x_k denotes the model trajectory represented by an ensemble member. The observation operator $\mathcal{H}_k$ is the observation-
 200 specific calculation that converts model output for ensemble member i into the quantity and support represented by y_k . The observation residual is then:

$$r_k^{(i)} = y_k - \mathcal{H}_k(x_k^{(i)}). \quad (2)$$

For scalar Gaussian likelihoods with observation standard deviation $\sigma_{y,k}$, openAMUNDSEN-DA computes ensemble member log likelihoods as Gaussian likelihood:

$$205 \quad \ell_k^{(i)} = -\frac{1}{2} \left(\frac{r_k^{(i)}}{\sigma_{y,k}} \right)^2 \quad (3)$$

and updates the normalized PF weights recursively:

$$\begin{aligned} a_k^{(i)} &= \log w_{k-1}^{(i)} + \ell_k^{(i)}, \\ w_k^{(i)} &= \exp \left(a_k^{(i)} - \text{LSE}(a_k) \right). \end{aligned} \quad (4)$$

Terms identical for all members are omitted because they do not affect normalized weights. Here, $\text{LSE}(a_k) = \log \sum_{j=1}^{N_e} \exp(a_k^{(j)})$ denotes the log-sum-exp normalization. The initial weights are uniform, $w_0^{(i)} = 1/N_e$. At subsequent events, the likelihood is
 210 multiplied by the carried prior weight as required for sequential importance sampling (Arulampalam et al., 2002; Chopin and Papaspiliopoulos, 2020). The normalized weights persist whenever resampling is skipped and reset to uniform only after actual resampling.



The prior ensemble is generated by perturbing meteorological forcing variables before each assimilation step. Air temperature is perturbed additively, precipitation multiplicatively and incoming shortwave radiation multiplicatively for non zero
 215 daytime values. Since relative humidity is a bounded percentage, perturbing it directly can create values outside the physically meaningful range or produce artifacts through clipping. We therefore treat humidity through dew point temperature, following the perturbation strategy used in snow reanalysis work and the Magnus humidity formulation (Fang et al., 2022; World Meteorological Organization, 2008). Dew point represents the actual moisture state of the air more directly, while relative humidity also changes when air temperature is perturbed. For each member, air temperature and relative humidity are first converted to
 220 dew point temperature with the Magnus constants $a = 17.62$ and $b = 243.12^\circ\text{C}$. The sampled humidity perturbation is then applied as an additive dew point offset, capped at the perturbed air temperature to maintain saturation consistency, and converted back to relative humidity.

The additive temperature and dew point perturbations are sampled from normal distributions, while precipitation and short-wave radiation factors are sampled from lognormal distributions. These forcing perturbation magnitudes are configured in the
 225 project YAML file and should be chosen carefully because they directly control ensemble spread and can strongly affect the DA update; the Rofental example values are reported in Table 3. Each sampled offset or factor is applied to all forcing files. Scientific stages require explicit seeds. Forcing perturbations use deterministic keyed random-number streams that combine the base seed, stage, event, member and variable; systematic resampling uses a separate key comprising the base seed, stage and event. This produces identical results regardless of worker scheduling, member ordering or partial rebuilding, while pro-
 230 ducing different perturbations for different propagation windows. Future work will extend the prior generation with spatially and temporally correlated perturbation fields, motivated by the sensitivity of snow DA to forcing-error characterization and by approaches that infer and spatially propagate meteorological forcing corrections from snow observations (Kumar et al., 2017; Oberrauch et al., 2024). In general, the generation of the prior ensemble by perturbing meteorological forcing variables follows snow model sensitivity studies showing that meteorological forcing errors, especially in precipitation, dominate physically
 235 based snow simulations (Raleigh et al., 2015; Günther et al., 2019). In addition, this forcing only prior helps to preserve each member’s mass and energy consistency (Oberrauch et al., 2025). The incorporation of snow model parameter sampling can be explored in future work and may support a better capture of melt phases controlled by albedo and liquid water retention.

After the comparison of observed and modeled values, normalized weights for the prior ensemble are computed (Fig. 1
 c). The normalized weights indicate how strongly an observation influences the selection of ensemble members. Hence, PF
 240 performance is commonly monitored with the effective sample size (ESS):

$$\text{ESS}_k = \left(\sum_{i=1}^{N_e} (w_k^{(i)})^2 \right)^{-1}. \quad (5)$$

Here, $w_k^{(i)}$ is the normalized PF weight of ensemble member i at assimilation step k , N_e is the ensemble size and $\sum_{i=1}^{N_e} w_k^{(i)} = 1$. The ESS ranges from 1 to N_e ; low values indicate that the weights are concentrated on few members, while values near N_e indicate flatter weights. The weighted analysis is defined before resampling and is used for posterior means, spreads, quantiles,
 245 maps, increments and benchmark diagnostics. When ESS falls below the threshold, systematic resampling creates the materi-



alized posterior ensemble that initializes subsequent propagation and assigns uniform weights to its children. When resampling is skipped, the workflow mirrors member directories for compatibility, but the weighted analysis remains the posterior and its member weights are carried to the next event. Skipped resampling therefore remains a Bayesian update; it does not mean that the observation was ignored.

250 The next propagation window receives freshly perturbed meteorological forcing regardless of whether resampling occurred. The public workflow term *rejuvenation* denotes this event-specific process-noise refresh, not a Markov chain Monte Carlo resample-move step. Forcing is rebuilt from the unmodified source data before the new perturbations are applied, so perturbation histories do not compound. This refresh helps preserve ensemble spread after selective updates and reduces the risk of sample impoverishment, a central limitation of sequential importance resampling in hydrologic DA (Moradkhani et al., 255 2005; Abbaszadeh et al., 2018). Efficient resampling and process-noise refreshes are important for high dimensional geophysical applications, where naive global particle filters can collapse unless ensemble size, localization or problem dimension are controlled (Snyder et al., 2008; Bengtsson et al., 2008). openAMUNDSEN-DA addresses this pragmatically through configurable PF parameterizations, domain scale scalar updates and optional subdomain execution; however, no formal localized PF is implemented yet (Farchi and Bocquet, 2018; van Leeuwen et al., 2019).

260 The diagnostic options of openAMUNDSEN-DA support the evaluation of DA experiments and the selected setting. Currently, the three benchmark skill scores comparing the posterior ensemble distribution including DA with results from the open loop run are computed and logged automatically:

$$\begin{aligned} \text{CRPSS} &= 1 - \frac{\text{CRPS}_{DA}}{\text{CRPS}_{OL}}, \\ \text{NER} &= 1 - \frac{\text{RMSE}_{DA}}{\text{RMSE}_{OL}}, \\ z\text{Skill} &= 1 - \frac{z\text{RMSE}_{DA}}{z\text{RMSE}_{OL}}. \end{aligned} \tag{6}$$

The root mean squared error (RMSE) measures the deterministic error between a model summary and the corresponding 265 observations, while the continuous ranked probability score (CRPS) evaluates the full ensemble predictive distribution against observations; lower RMSE and CRPS values indicate better agreement (Cluzet et al., 2021; Micheletty et al., 2022). The resulting skill scores express improvement relative to the open loop: values closer to 1 indicate stronger improvement, 0 indicates no improvement and negative values indicate degradation. The continuous ranked probability skill score (CRPSS) is based on the CRPS ratio, the normalized error reduction (NER) on the RMSE ratio (Hou et al., 2021), and $z\text{Skill}$ on 270 residuals normalized by the effective station uncertainty (Oberrauch et al., 2025). In DA event benchmark plots, prior scores use the carried weights entering the event and posterior scores use the recursively updated event weights. After resampling, the next prior begins with uniform weights. An increase from prior to posterior therefore indicates that the current observation improved agreement with the corresponding diagnostic. Benchmark categories classify how closely a diagnostic is tied to the update being assessed: *assimilation fit* is the update fit to the assimilated variable and date, *semi-independent* evaluations



275 provide transfer or consistency evidence after related observations have already been assimilated but not at this specific DA event, and *independent* is the strongest automated benchmark category because the variable has not been assimilated yet.

In the following, we describe different snow observation types currently available within openAMUNDSEN-DA including their support and uncertainty treatment (Tab. 1). Station snow depth and SWE are point scale observations and compared to simulations from the corresponding grid cell, not basin means. This keeps the limited spatial representativeness of flat
 280 field station observations explicit (Grünwald and Lehning, 2015). At each assimilation step, station observations enter the likelihood with uncertainty-based weighting, allowing the framework to propagate point scale uncertainty through the ensemble without imposing a direct gridded correction (Cluzet et al., 2022). The base uncertainty for a station observation is computed the following:

$$\sigma_{s,k} = \sqrt{(p_s \times y_{s,k})^2 + (\sigma_s^{\text{abs}})^2} \quad (7)$$

285 where s is the station, k the time step, p_s the relative station uncertainty factor, $y_{s,k}$ the in-situ snow observation and σ_s^{abs} the station specific absolute uncertainty floor. If only one station is active, the sigma can be inflated by a single station factor so that one point observation cannot constrain the full domain as strongly as a station network. Assuming conditionally independent station errors, the ensemble member log likelihood is summed over all stations:

$$\ell_k^{(i)} \propto -\frac{1}{2} \sum_{s \in S_k} \left(\frac{r_{s,k}^{(i)}}{\sigma_{s,k}} \right)^2 \quad (8)$$

290 where s indexes an individual station, S_k is the set of stations active at assimilation step k , i indexes the ensemble member being evaluated and $r_{s,k}^{(i)}$ is the residual between the observation at station s and that member. This computation represents a standard step of a PF weighting approach including an effective observation uncertainty that addresses measurement uncertainty and point-to-domain representativeness (Evensen et al., 2022; Grünwald and Lehning, 2015).

For fSCA, openAMUNDSEN-DA evaluates the model equivalent over the same observation valid spatial support as the
 295 satellite product. With the threshold operator, each valid grid cell of each ensemble member is classified as snow covered when simulated snow depth exceeds the user configured snow presence threshold h_0 . Aggregating these binary classifications over the valid support gives the member-specific fSCA used in the likelihood, while aggregating them across ensemble members yields model-side snow cover probability maps.

WSF is computed analogously as the number of valid pixels classified as wet divided by all valid pixels. For satellite
 300 products, cloud covered pixels, no data pixels and land cover classes excluded by the project mask are removed from the valid support before observations and model equivalents are aggregated. These pixels are therefore not treated as high uncertainty observations. Applying the same grid cell selection to observations and simulations prevents comparing a visible area satellite fraction with a full-domain model fraction, a common source of representativeness error in snow DA (Aalstad et al., 2018).

The likelihood needs one observation sigma for the aggregated fSCA value. openAMUNDSEN-DA can obtain this sigma in
 305 two alternative ways. In formula mode, sigma is computed internally from scene summary quantities, including the observed



fSCA, number of valid pixels, cloud fraction and configured floor and scale parameters. In uncertainty-layer mode, sigma is derived from a gridded uncertainty layer that was either provided with the observation product or generated before assimilation with openAMUNDSEN-DA preprocessing tools. A larger sigma weakens the observation, produces flatter particle weights and reduces the chance of resampling, while a smaller sigma sharpens the likelihood, concentrates weights and makes resampling more likely.

The Rofental fSCA setup uses uncertainty layer mode with the valid-support mean uncertainty, $\bar{u}_k$. For satellite-based fSCA, the generated baseline pixel uncertainty is

$$u_{\text{base}}(z) = u_{\text{min}} + 2(u_{\text{max}} - u_{\text{min}}) \frac{\min(z, 100 - z)}{100}, \quad 0 \leq z \leq 100 \quad (9)$$

where z is the pixel snow cover value on a 0 to 100 scale and u_{min} and u_{max} are the minimum and maximum baseline pixel uncertainties. This baseline assigns lower uncertainty to fully snow covered and snow free pixels and the highest baseline uncertainty to intermediate, mixed pixels. Forest, shadow or product specific penalties can be added for valid pixels before the final uncertainty layer is clipped to $[0, 100]$. Clouds and no data classes remain masked. The configured support aggregate $\bar{u}_k$ at assimilation step k is then mapped to the likelihood sigma as

$$\sigma_{\text{fSCA},k} = \max\left(\sigma_{\text{min}}, \frac{\bar{u}_k}{100}\right). \quad (10)$$

Here, σ_{min} is the minimum likelihood sigma. If formula mode is selected instead, openAMUNDSEN-DA uses an internal summary formula with optional binomial variance, an uncertainty floor, cloud inflation and an absolute minimum sigma. When binomial mode is disabled and a fixed observation sigma is configured, this fixed value acts as an additional lower bound. For binary wet snow maps, the same uncertainty-layer infrastructure can generate uncertainty fields from a constant base uncertainty plus penalties for valid wet and dry pixels.

Using an algorithm based on elevation bands, we compute the WSLA for the domain. This computation condenses an elevation dependent energy exchange state into one scalar and is applied identically to observed and modeled wet snow maps, the open loop, ensemble members, benchmarks and maps. Rather than weighting a high dimensional binary Sentinel-1 mask pixel by pixel, openAMUNDSEN-DA reduces the wet snow map to WSF or WSLA scalars before PF likelihood weighting. The satellite product provides a binary wet- or dry-snow classification, while model pixels are classified instantaneously using a configurable threshold on simulated volumetric liquid water content. This threshold addresses the sensitivity of C-band wet snow retrievals to small liquid water amounts (Rottler et al., 2024; Cluzet et al., 2024). WSF is computed in 100 m elevation bands and smoothed with a centered three-band median. All downward crossings of the 0.5 WSF threshold are located and linearly interpolated between adjacent band centers. The uppermost valid crossing is selected as the WSLA; profiles without a crossing are unavailable. Consequently, Sentinel-1 maps can complement fSCA by constraining melt onset and liquid water evolution rather than snow extent alone (Cluzet et al., 2024).



Table 1. Snow observation types for assimilation supported by openAMUNDSEN-DA v0.9, their model equivalents and support and uncertainty treatment.

Type	Observed variable [unit]	Model equivalent	Support and uncertainty treatment
HS	In situ snow depth [m]	Snow depth of grid cell	Station specific uncertainty; all stations contribute to domain-level weighting
SWE	In situ snow water equivalent [mm]	Snow water equivalent of grid cell	Station specific uncertainty; all stations contribute to domain-level weighting
fSCA	Fractional snow covered area [-]	Fraction of grid cells with snow above a user defined threshold	Cloud, land cover and uncertainty layers define spatial support and uncertainty
WSF	Wet snow fraction [-]	Fraction of grid cells with liquid water above a user defined threshold	Categorical support, land cover exclusion and product specific uncertainty settings
WSLA	Wet snow line altitude [m]	Interpolated uppermost downward crossing of smoothed elevation-band WSF	Derived from support aware elevation-band WSF; undefined crossings are skipped

4 Case study

4.1 Study area and data

The following case study from the Rofental research catchment (Ötztal Alps, Austria; 99.40 km²; Fig. 3) illustrates the capabilities of the presented snow data assimilation framework and outlines the typical steps of an openAMUNDSEN-DA workflow.

340 The Rofental and the Ötztal Alps have repeatedly served as study sites for openAMUNDSEN snow modeling experiments, including a multilevel spatiotemporal evaluation of the modeling results using gridded datasets and time series of various sources (Hanzer et al., 2016, 2018; Rottler et al., 2024). We model the Rofental in 100 m spatial resolution and 3-hourly time steps for the winter season 10/2022 to 06/2023 using an energy balance approach and the 'multilayer' layering scheme, which differentiates up to three snow layers (Essery, 2015; Strasser et al., 2024). The model domain spans elevations from 1905 to

345 3695 m a.s.l., with a mean elevation of 2894 m a.s.l.

The snow simulations use a prepared meteorological forcing baseline derived from observations at the stations Bella Vista (2805 m a.s.l.), Proviantdepot (2659 m a.s.l.) and Latschbloder (2919 m a.s.l.) (Fig. 3 a). The stations are part of the upper Rofental monitoring infrastructure, for which recent meteorological and snow hydrological observations are documented by Warscher et al. (2024). The Rofental model setup, including its meteorological stations, serves as the standard test dataset for

350 evaluating new openAMUNDSEN developments. It is distributed with the original snow model source code and is also bundled with the DA framework as sample data for new users' initial assimilation experiments. The station-based forcing is interpolated to the model grid using a combined regression and inverse distance weighting approach. In all simulations, precipitation is corrected for undercatch using functions provided by Kochendorfer et al. (2017), and lateral snow redistribution processes are



considered applying snow redistribution factors based on the concept of negative topographic openness (Yokoyama and Pike,
 2002; Hanzer et al., 2016; Strasser et al., 2024). Because the Rofental setup is a well-tested openAMUNDSEN domain, the
 unmodified forcing baseline produces an open loop simulation that is already close to the available snow observations. For
 an illustrative DA workflow, this leaves little room to demonstrate how PF weighting, resampling, posterior increments and
 diagnostics respond to informative observations. We therefore use a modified forcing baseline as a controlled demonstration
 case, in which station precipitation was deliberately reduced by 40 % to introduce a controlled mismatch in precipitation
 forcing. The open loop uses this modified baseline without stochastic perturbations, while the ensemble members start from
 the same baseline and then receive the stochastic forcing perturbations configured in the DA project. Snow observations from
 Proviantdepot and Latschbloder provide snow depth used in the DA and benchmarking workflows.

The satellite snow observation data comprise Sentinel-2 fractional snow cover and Sentinel-1 wet snow maps. These data
 sets were already available for the Rofental from previous investigations (Rottler et al., 2024) and originate from the AlpSnow
 project (<https://alpsnow.enveo.at/>; last access 16/07/2026), a science activity within the Alpine Regional Initiative from the
 European Space Agency (ESA). Both gridded products undergo support aware preprocessing, uncertainty handling, and land
 cover masking before entering the sequential particle filter updates. The satellite snow cover products are summarized as fSCA,
 WSF, and WSLA (see Tab. 1).

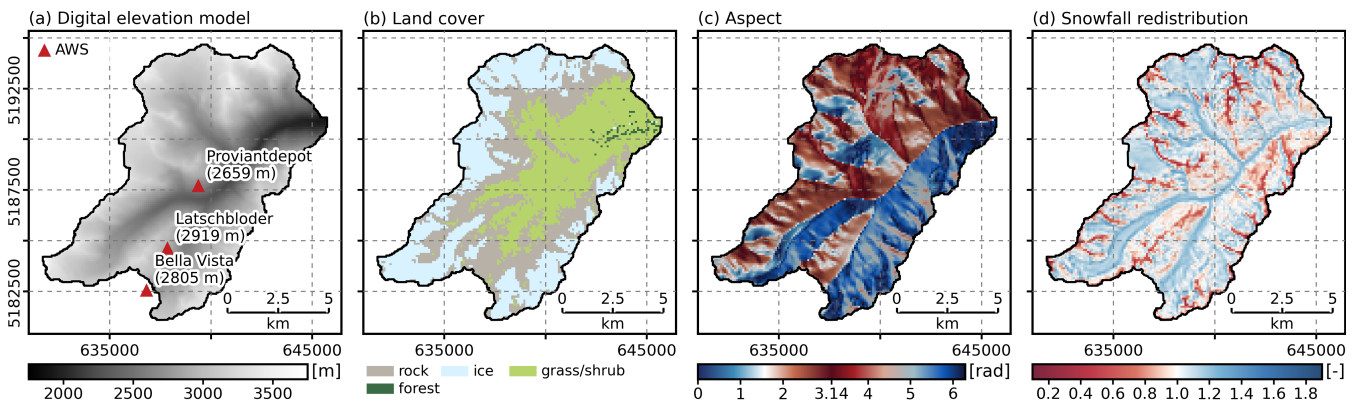


Figure 3. The Rofental research catchment (Ötztal Alps, Austria): (a) digital elevation model (DEM) with meteorological stations, (b) simplified land-cover classes regrouped from the EUSALP LULC map 2020 (Marsoner et al., 2023b), distributed under the CC0 1.0 license and described by Marsoner et al. (2023a), (c) aspect and (d) snowfall redistribution. To represent lateral snow redistribution, the spatially interpolated snowfall field is multiplied by a factor derived from topographic openness (Hanzer et al., 2016; Strasser et al., 2024).

4.2 Data assimilation experiment

The following experiment is intended to illustrate the capabilities of openAMUNDSEN-DA and to make the sequential update
 logic and its physical consequences visible when the framework is applied to a high alpine setting. We analyze one snow
 season from accumulation through melt onset to late season depletion to demonstrate how snow observations influence particle



weights, resampling decisions, diagnostics and distributed snow state fields. For clarity, we split the DA experiment into three seasonal periods: (i) early and high season station updates, (ii) an April fSCA update and the May WSLA update and (iii) late season fSCA assimilation (Tab. 2). The eight assimilation steps in this showcase application represent a balance between demonstrating multiple examples and functionalities and maintaining clarity.

The assimilation time steps and all DA configurations, including the definition of the prior ensemble, observation operators and likelihood assumptions, are defined by the user in the respective configuration files of the DA project (Fig. 2). At each nonfinal step, prior ensemble propagation is followed by event-specific model equivalent calculation and recursive likelihood weighting. ESS then determines whether the posterior is materialized by resampling or whether the weighted member set is carried forward, and rejuvenation refreshes the process noise for the next propagation window. The experiment is therefore read as one seasonal sequence of DA updates configured within an openAMUNDSEN-DA project. The following discussion focuses on station snow depth, fSCA and WSLA (Fig. 4 f).

The Rofental DA project uses 30 ensemble members, the fixed base seed 1415935400 and resampling when ESS falls below 70 % of the ensemble size (Tab. 3). The prior ensemble is generated by perturbing air temperature with additive offsets of $\sigma_T = 1.0\text{K}$, precipitation with lognormal factors using $\mu_P = -0.055$ and $\sigma_P = 0.6$, dew point with $\sigma_{RH} = 1.2\text{K}$ and shortwave radiation with daytime multiplicative factors of $\sigma_{SW} = 0.15$. The same perturbation scales are used for rejuvenation after nonfinal assimilation steps, but the keyed random-number streams produce new perturbations for every propagation window.

The observation operators and likelihood settings determine how each data source enters the PF update. Station snow depth is compared directly to model snow depth. The station uncertainty values are user-assigned likelihood settings that represent effective measurement and representativeness uncertainty rather than calibrated sensor-error estimates. In this case study, Proviantdepot uses 10 % relative uncertainty with a 0.10 m absolute floor, while Latschbloder uses 500 % and a 0.30 m floor to give it weaker influence and demonstrate station-specific likelihood weighting. fSCA is computed from a snow depth threshold of $h_0 = 0.03\text{m}$. Its likelihood sigma uses the valid-support mean of the uncertainty layer with a minimum of 0.05; the realized values are 0.1012 on April 26 and 0.1014 on May 26. Wet snow is classified from a 0.4 % liquid water threshold. The WSLA operator uses 100 m elevation bands, the centered three-band median and the interpolated uppermost downward 0.5 crossing. Its likelihood sigma is 200 m, and at least 0.95 of the model members must provide a finite WSLA.

We first assimilate station observations during the core winter period. Because the Rofental is fully snow covered at this time, assimilating fSCA alone would have only minimal impact on the model ensemble. The assimilated snow depth observations come from the two stations within the model domain: Proviantdepot and Latschbloder. We report results from Proviantdepot, which we consider more representative and subject to smaller effective uncertainty. Through Eq. 8, the larger sigma reduces the contribution of Latschbloder residuals to the summed station log likelihood. The ESS values for DA1–DA8 are 25.3, 8.1, 16.6, 25.3, 14.7, 24.7, 17.5 and 18.3, respectively (Fig. 4 e). DA2, DA3, DA5, DA7 and DA8 trigger resampling, while DA1, DA4 and DA6 retain their weighted member sets. At DA1 and DA4, the observations still change the normalized weights and weighted diagnostics. These weights are carried until the next actual resampling, so skipped resampling is a Bayesian update rather than an absence of assimilation. The resampling threshold of 0.7 is a configured case-study choice, not an optimized universal setting.

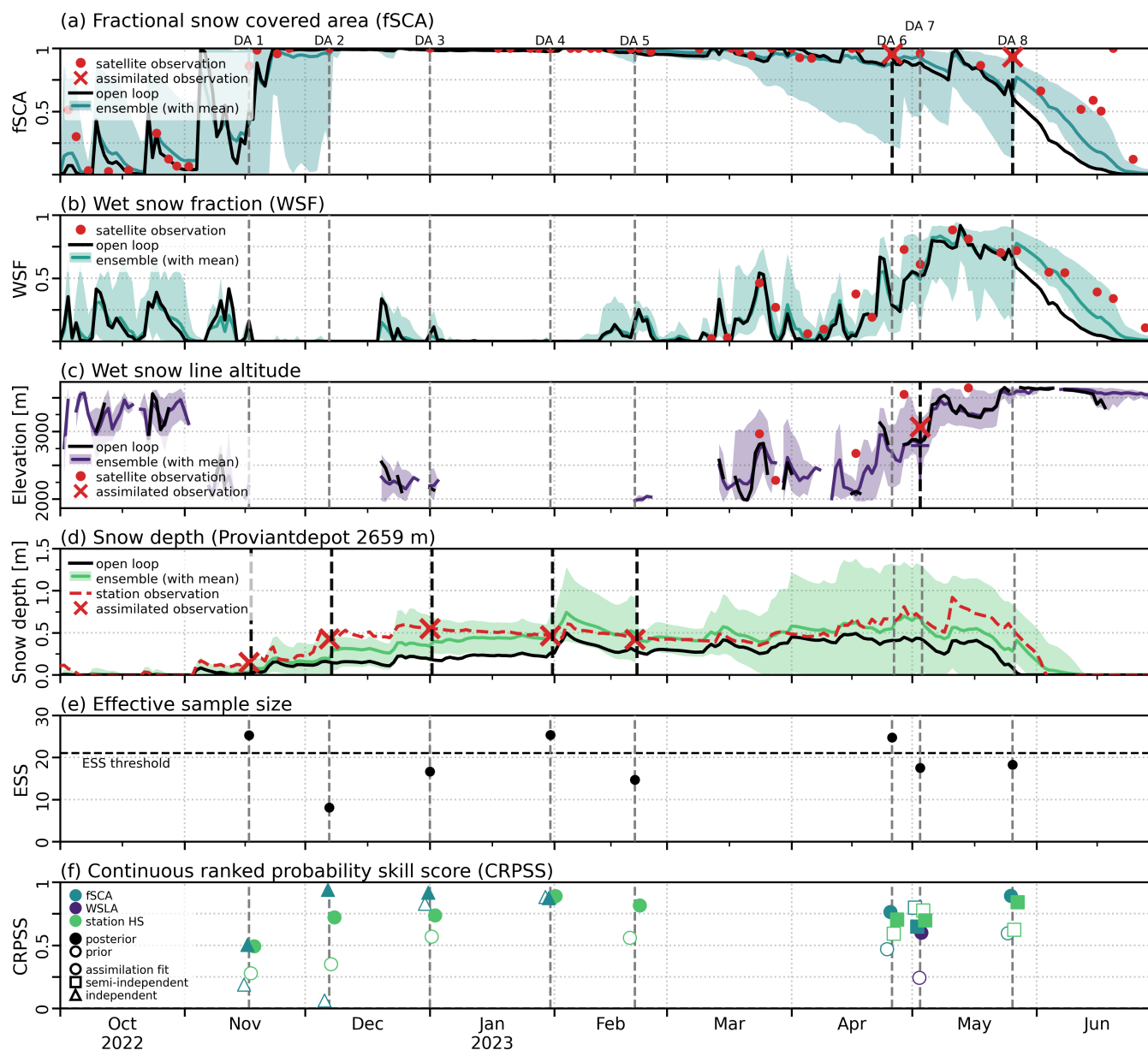


Figure 4. Open loop and ensemble trajectories with snow data assimilation for the Rofental catchment in winter 2022/2023, simulated with openAMUNDSEN-DA: (a) fractional snow covered area (fSCA), (b) wet snow fraction (WSF), (c) wet snow line altitude (WSLA), (d) in-situ snow depth from station Proviantdepot, (e) effective sample size (ESS) and (f) the Continuous Ranked Probability Skill Score (CRPSS). Vertical dashed lines mark the dates of the assimilation events. Darker dashed lines identify the panel corresponding to the assimilated variable, and X markers indicate observations used for assimilation.



Table 2. Date and snow observation type of assimilation events in the openAMUNDSEN-DA workflow example demonstration.

Date	Observation type
2022-11-17	Station snow depth
2022-12-07	Station snow depth
2023-01-01	Station snow depth
2023-01-31	Station snow depth
2023-02-21	Station snow depth
2023-04-26	Snow cover fraction
2023-05-03	Wet snow line altitude
2023-05-26	Snow cover fraction

At DA5, the station snow depth observation concentrates the recursively updated importance weights and triggers systematic resampling (Fig. 5 e). Given the high effective uncertainty at Latschbloder, even large residuals there have little influence on the summed station likelihood. The station snow depth CRPSS increases from 0.56 to 0.81 (Fig. 4 f). DA6 assimilates fSCA on April 26. It improves the assimilation-fit diagnostics, but ESS remains above the threshold, so the DA6 posterior weights persist into the DA7 prior instead of being reset.

The distributed modeling results illustrate the spatial effects of scalar domain-level likelihoods, showing how openAMUNDSEN-DA adjusts ensemble member probabilities and posterior composition rather than individual pixels (Figs. 6 and 7). DA7 assimilates the May 3 WSLA observation at its matched instantaneous model state. The weighted prior WSLA is about 2810 m and the weighted analysis reaches about 2900 m, closer to the observed value of about 3070 m (Fig. 6 e–h). The WSLA CRPSS increases from 0.24 to 0.60. At the same event, the semi-independent fSCA, snow depth and SWE scores decrease modestly but remain positive. This indicates a tradeoff from scalar domain-level weighting: selecting trajectories that improve the WSLA does not guarantee simultaneous improvement in every related snow diagnostic. The spatial snow depth increment remains moderate and topographically structured (Fig. 6 i–l).

On May 26, DA8 assimilates fSCA over the valid satellite support and excludes cloud-covered pixels (Fig. 7 d). The event ranks the remaining trajectories clearly enough to trigger resampling (Fig. 5 h). Its fSCA CRPSS increases from 0.60 to 0.89. The station time series remain useful as qualitative consistency checks after the last station assimilation, but this controlled demonstration does not establish a causal or generally robust improvement in continuous station performance.

The Rofental example illustrates the capability of openAMUNDSEN-DA to trace each DA event, including the ESS decision, the likelihood response, the posterior ensemble, and the distributed snow state increment. All figures and maps are generated automatically for each DA experiment and can be customized via the openAMUNDSEN-DA configuration for the logging and reporting workflow, enabling the same diagnostic structure to be reused across DA projects and study areas. Our example outputs demonstrate workflow behavior and diagnostic traceability. They do not represent a final DA experiment with strict



Table 3. Selected data assimilation settings for the Rofental case study defined using the configuration files including ensemble and filter parameters, and forcing perturbation, observation operators and uncertainty settings.

<i>Model ensemble and particle filter</i>		
Prior ensemble	Members	30
	Base seed	1415935400
Resampling	ESS ratio	< 0.7
Rejuvenation	Forcing scales	Same as prior
<i>Forcing perturbations</i>		
Air temperature	Perturbation	Additive
	Standard deviation	$\sigma_T = 1.0 \text{ K}$
Precipitation	Perturbation	Lognormal factor
	Distribution	$\mu_P = -0.055, \sigma_P = 0.6$
Relative humidity	Perturbation	Dew-point transform
	Dew-point scale	$\sigma_{RH} = 1.2 \text{ K}$
Shortwave radiation	Perturbation	Multiplicative
	Standard deviation	$\sigma_{SW} = 0.15$
<i>Observation operators</i>		
Station snow depth	Direct model equivalent	Grid cell value
Snow cover fraction	Snow depth threshold	$h_0 = 0.03 \text{ m}$
Wet snow	LWC threshold	0.4%
Wet snow line	Elevation bands	100 m
	Crossing	Uppermost downward 0.5
<i>Uncertainty and support</i>		
Station snow depth	Proviandepot uncertainty	10 %; 0.10 m floor
	Latschbloder uncertainty	500 %; 0.30 m floor
Snow cover fraction	Sigma mode	Uncertainty-layer mean
	Minimum sigma	0.05
Wet snow line	Elev. band size	100 m
	Sigma	200 m
	Model finite fraction	0.95

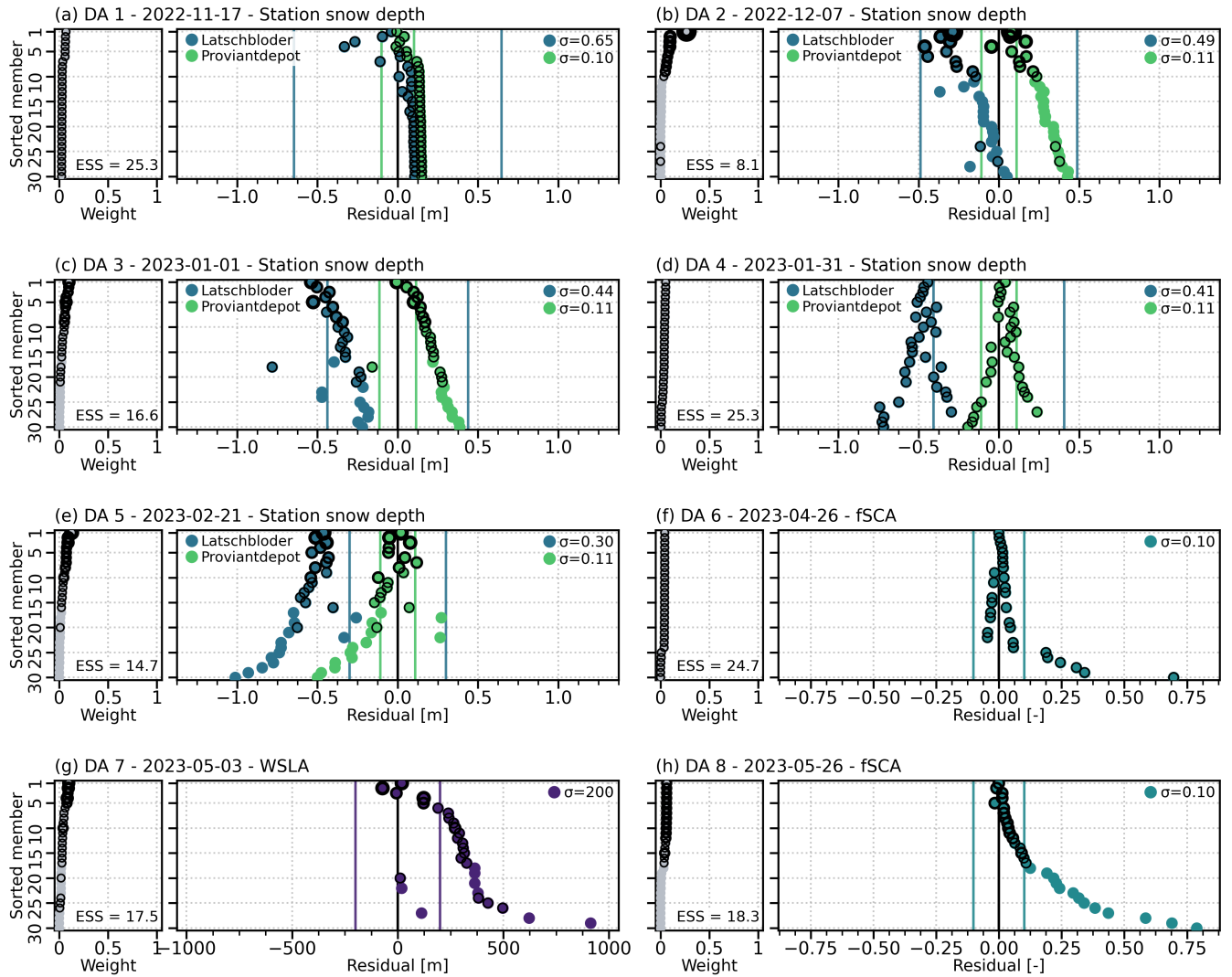


Figure 5. Recursively updated particle filter weights for the snow data assimilation events in the Rofental case study (a–h), simulated with openAMUNDSEN-DA. Each event panel displays sorted normalized weights alongside the corresponding observation residuals; colors denote the assimilated snow observation type. Circles mark individual members and rings around circles indicate members selected during resampling.

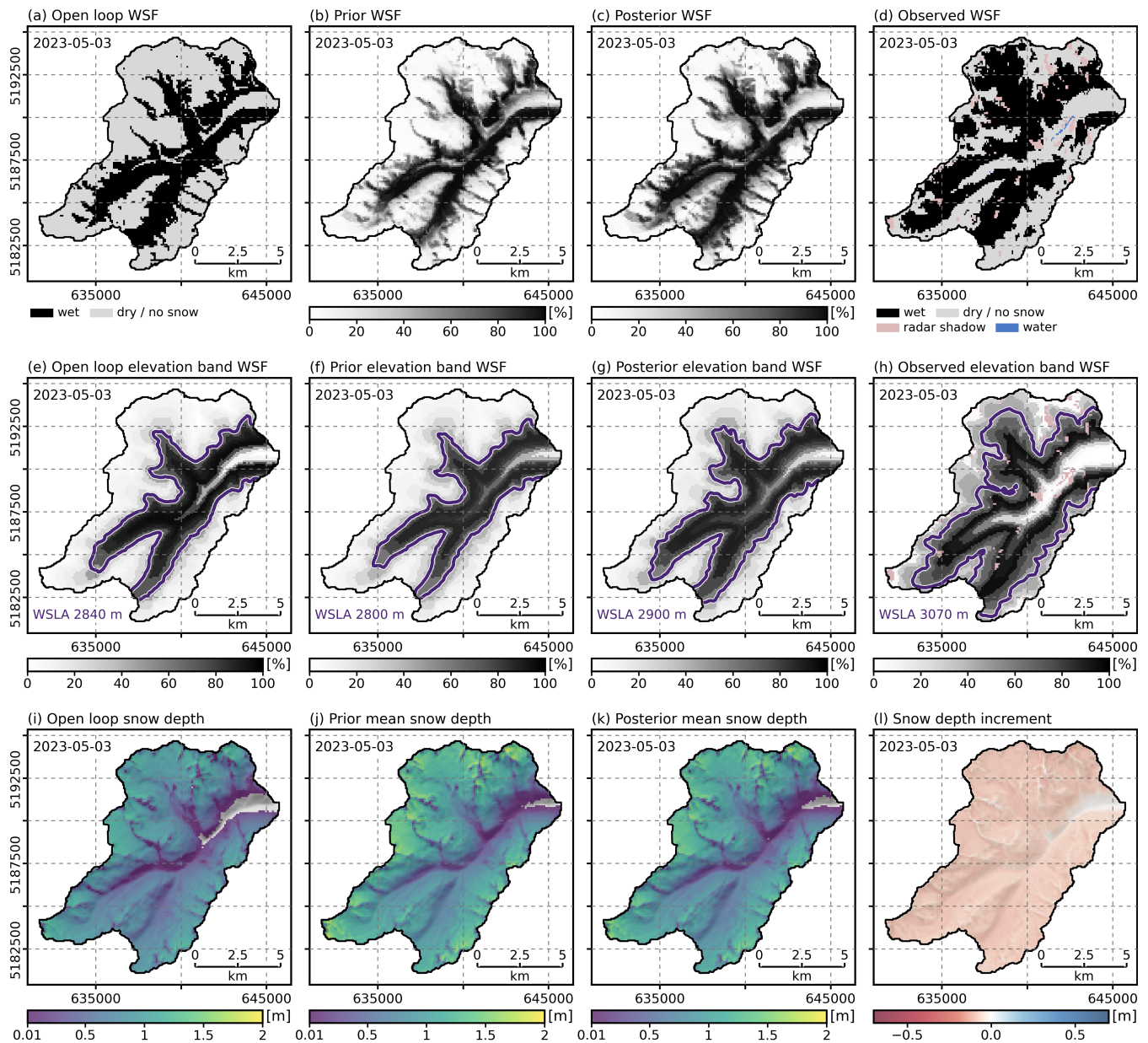


Figure 6. Spatial diagnostics for the DA7 wet snow line altitude (WSLA) assimilation event on 03/05/2023. Panels (a–d) show open loop, weighted prior, weighted analysis and observed wet snow fraction (WSF). Panels (e–h) show the corresponding elevation-band WSF in 100 m bands and the interpolated uppermost WSLA. Panels (i–l) show open loop snow depth, weighted prior and analysis ensemble mean snow depth and the analysis increment. The observed wet-snow product in panel (d) was provided by ENVEO within the ESA AlpSnow project and is described by Rottler et al. (2024).

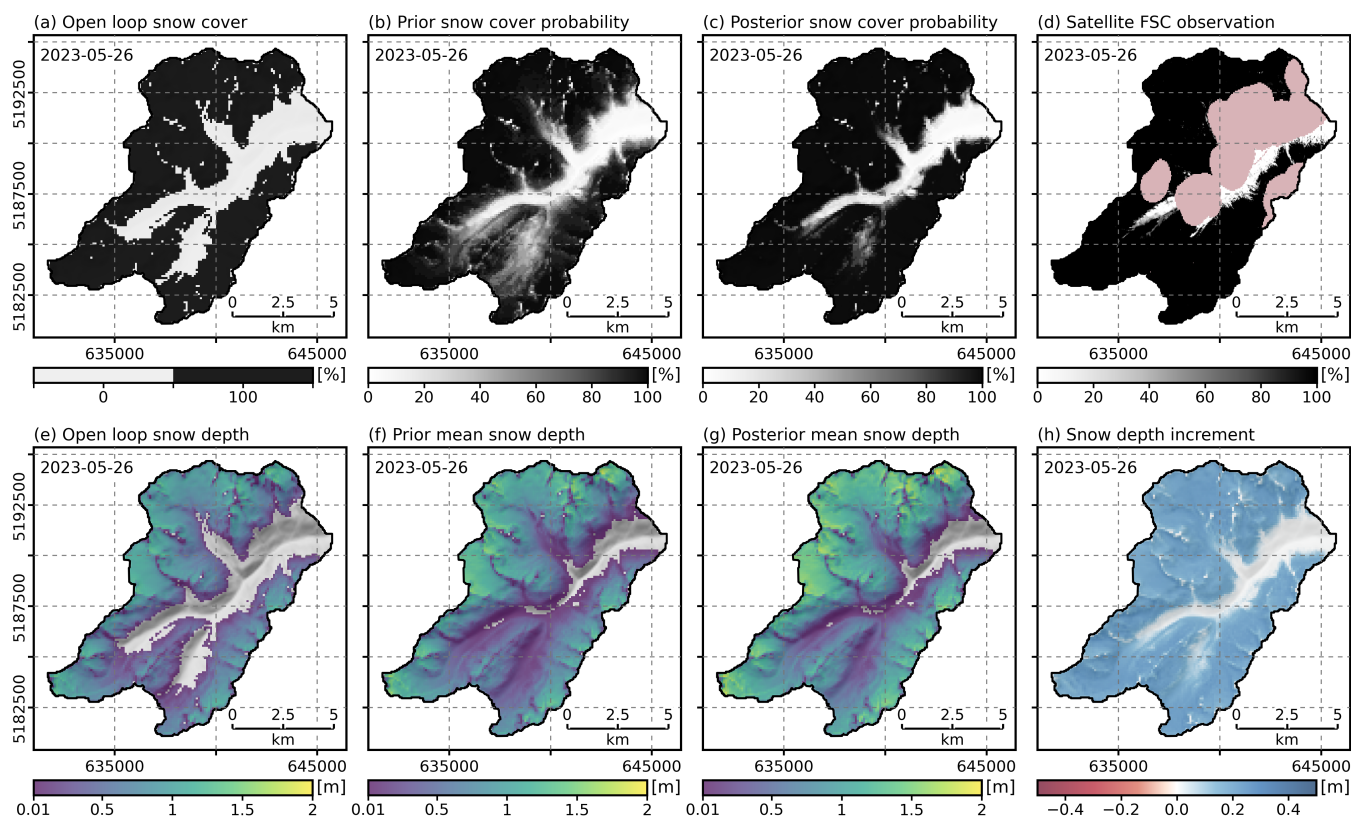


Figure 7. Spatial diagnostics for the DA8 fSCA assimilation event on 26/05/2023. Panels (a–d) show open loop snow cover, weighted prior and analysis snow cover probability and the satellite fractional snow-cover observation. Panels (e–h) show open loop snow depth, weighted prior and analysis ensemble mean snow depth and the analysis increment. The observed fractional snow-cover product in panel (d) was provided by ENVEO within the ESA AlpSnow project and is described by Rottler et al. (2024).

independent validation. The example shows that openAMUNDSEN-DA can provide a foundation for developing new snow DA methods and operational applications and is well suited for teaching DA in advanced snow-hydrological modeling.

5 Discussion

openAMUNDSEN-DA v0.9 provides a complete, sequential PF workflow built around the open source openAMUNDSEN mountain snow model. The framework covers all procedural steps required for DA with openAMUNDSEN: preprocessing of snow observational data, event scheduling, prior ensemble generation, event specific weighting, ESS based resampling decisions, posterior initialization, rejuvenation, benchmark diagnostics, and automatic generation of result figures and maps. Hence, openAMUNDSEN-DA offers a traceable connection between a state-of-the-art distributed intermediate complexity snow hydrological model, support aware snow observations, transparent uncertainty assumptions and reproducible project



execution. The Rofental case study demonstrates how station snow depth, WSLA and fSCA updates and their impact on the
 440 snow model ensemble can be tracked and interpreted.

Available snow DA systems provide important context for our development without occupying the same software niche. For example, CrocO implements spatialized PF variants (Cluzet et al., 2021) within a dedicated snowpack framework built around Crocus (Vionnet et al., 2012; Lafaysse et al., 2026); MuSA offers a broad, modular toolbox with multiple filters, smoothers and joint assimilation options (Alonso-González et al., 2022); and FSM2OSHD exemplifies operational Swiss snow
 445 hydrological modeling with recent fully distributed assimilation experiments (Mott et al., 2023; Oberrauch et al., 2026). In contrast, openAMUNDSEN-DA focuses on coupling the fully distributed openAMUNDSEN snow model to an event driven DA workflow configured via documented YAML files, developed as an open source project and distributed as an easy to install and use Python library in a portable containerized structure. Its methodological assumptions, observational support and diagnostic outputs are transparent to the user and also aim to support large scale (regional) applications. openAMUNDSEN-DA
 450 experiments from controlled case studies can be easily transferred to new regions or operational settings.

The Rofental example demonstrates the sequential PF updates and provides insights into available diagnostics. Satellite driven fSCA, WSLA and station based updates can be investigated alongside each other with the same tools. The computation of diagnostics of (semi-)independent snow variables is an important performance and consistency check. Different uncertainty values can be assigned to stations. openAMUNDSEN-DA provides all required tools to conduct dedicated Leave-One-Out
 455 Cross Validation (LOOCV) experiments, holdout experiments, and Observing System Simulation Experiment (OSSE) style tests, and independent spatial snow datasets can be incorporated for further evaluation.

The transparent DA workflow also supports identifying the limitations of the DA for snow data. Station observations only provide very local evidence in often highly complex terrain, not basin means, and satellite snow data are not always available at the desired time step; clouds, no data areas and land cover types often need to be masked. Consequently, selected likelihood
 460 sigmas, uncertainty layers, station trust settings and support thresholds are very important DA parameters and need to be documented for each experiment. The WSLA concept is promising because it constrains melt timing and liquid water evolution, but reducing available distributed data to a WSLA also compresses aspect- and slope dependent melt patterns into a single domain level metric. This abstraction is useful for a robust scalar likelihood target, but it cannot represent the full topographic variance in wet snow dynamics of Sentinel-1 melt state assimilation (Cluzet et al., 2024). More broadly, snow observation
 465 error varies across space, time and snow state regimes and dynamic observation uncertainty is an important direction for future developments in snow DA (Dunmire et al., 2026).

At the algorithmic level, scalar weighting at the domain scale is a pragmatic design choice. It intentionally reduces the dimensionality of the PF update, making the workflow faster and more applicable to large scale applications, more robust and interpretable, but it lacks formal localization. Executing subdomains independently benefits larger scale applications by
 470 partitioning the domain into separate regional DA problems. This subdomain mode is also fully compatible with openAMUNDSEN's intermediate complexity modeling approach, allowing large areas to be divided into subdomains of any desired number and size. In the current implementation, however, no DA information is transferred between subdomains. The challenge of spatial information transfer is a central theme in current snow DA research, especially in the context of sparse observations



and heterogeneous mountain terrain (Alonso-González et al., 2023; Mazzolini et al., 2025). Future large scale applications can
475 apply and further optimize the subdomain approach available within openAMUNDSEN-DA. Careful treatment of support, un-
certainty and possible information transfer will be needed. Heterogeneous subregions may also motivate exploratory work on
complexity aware spatial resolution or parameterization choices to balance physical detail and computational cost. The current
workflow, which assimilates one observation type per event, does not yet support joint multivariate updates, even though snow
depth, SCF, WSF and WSLA constrain complementary parts of the seasonal snowpack. Enabling multivariate assimilation
480 hence will be a natural next extension of openAMUNDSEN-DA. The current implementation already provides the required
event structure, diagnostics and output products to test such extensions.

6 Conclusions

openAMUNDSEN-DA v0.9 is an open source snow DA framework built around the distributed, medium complexity snow
model openAMUNDSEN. The framework closely follows the configuration driven philosophy of openAMUNDSEN and snow
485 model configurations are kept separate from the DA specific configurations. The assimilation of snow observations is based
on a sequential PF at the model domain scale. The domain scale scalar weighting is a pragmatic design choice made to
match the openAMUNDSEN application focus, reduce the dimensionality of the PF update and make the workflow fast,
applicable for large areas, and more robust and interpretable. openAMUNDSEN-DA combines observation preprocessing
with a project pipeline that orchestrates the configured DA workflow. The pipeline controls event scheduling and ensemble
490 propagation, computes support aware model equivalents and likelihood weights, applies resampling and rejuvenation, and
generates benchmark scores, plots, maps and reports. Prior uncertainty is represented by perturbing meteorological forcing.
The development focus of openAMUNDSEN-DA is on a flexible and easy to apply snow DA framework with a transparent
and consistent workflow that can be used in research, operational applications and teaching.

The showcase study from the Rofental research catchment illustrates the DA project structure and the reusable diagnostic
495 workflow. In this experiment, we assimilate in-situ snow observations, wet snow information via the WSLA, and satellite
derived fSCA in a sequential update sequence. The results show how different snow observation types become informative at
different times of the season, how members are weighted and resampled, and how domain level likelihoods influence distributed
snow states through member selection. As an open source, Python based library with a modular, configurable diagnostic design,
openAMUNDSEN-DA provides an ideal platform for future development and reproducible regional applications in snow DA.
500 Next steps are more demanding regional and methodological studies. Subdomain applications can test localization approaches
and spatial information transfer, dynamic observation uncertainty and scalable diagnostics. Furthermore, method development
should also target multivariate updates, smoother or reanalysis workflows, model parameter perturbations and the assimilation
of additional snow observation types.



Code and data availability. The current openAMUNDSEN-DA source code and documentation are available at <https://github.com/openamundsens/openamundsens-da> and <https://doc-da.openamundsens.org/>, respectively (last access: 29 July 2026). The software is distributed under the MIT License. The exact version used for this study, v0.9.4, is archived on Zenodo (<https://doi.org/10.5281/zenodo.21677046>; Wagner et al., 2026). This archive contains the complete Rofental configuration and input files as well as the software routines required to reproduce the simulations, analyses and figures. The archived dependency constraints specify openAMUNDSEN v1.2.1; this version is archived on Zenodo (<https://doi.org/10.5281/zenodo.19108928>) and its source code is available under the MIT License at <https://github.com/openamundsens/openamundsens/releases/tag/v1.2.1> (last access: 29 July 2026) and is described by Strasser et al. (2024). The meteorological forcing and in situ snow observations originate from the upper Rofental data set, which is available under the Creative Commons Attribution 4.0 International License from GFZ Data Services (<https://doi.org/10.5880/fidgeo.2023.037>; Department of Geography, University of Innsbruck, 2024) and documented by Warscher et al. (2024). The land-cover input was derived from the EUSALP LULC map 2020, which is available from figshare under the CC0 1.0 license (<https://doi.org/10.6084/m9.figshare.21770441.v1>; Marsoner et al., 2023b) and described by Marsoner et al. (2023a). The Sentinel-1 wet-snow and Sentinel-2 fractional snow-cover products were provided by ENVEO within the ESA AlpSnow project and are described by Rottler et al. (2024).

Author contributions. FW developed the openAMUNDSEN-DA software code, conducted the case study, produced the case study figures and wrote the first version of the manuscript. ER supported the design and the development of openAMUNDSEN-DA, the writing of the manuscript and produced the schematic overviews. US is the developer of the original AMUNDSEN snow model, the PI of the project *Fram3S* which provides the framework for the development of openAMUNDSEN-DA, and also supported the writing of the manuscript. All authors continuously participated in the discussions of the architecture of the system, its application and the results, and provided helpful comments and suggestions.

Competing interests. The authors declare that they have no conflict of interest.

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